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Review Article

Detection of Driving Distractions and Their Impacts

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For decades, road crashes have caused many deaths and injuries and generally have had a severe social and economic impact on societies. According to studies, driver distraction has led to an increase in driving-related risks. In recent years, there have been more distracting factors that commonly affect drivers, highlighting the need for a resolution. Therefore, as technology is becoming more advanced, there is an opportunity to minimize these risks, for which driver distraction detection would be required. As there are a variety of distractions that might affect drivers and their performance, there are many studies focusing on this topic. To better understand the field of driver distraction detection, this paper has reviewed the existing studies in this field. For this purpose, different variables of the existing methodologies and experimental setups are identified and explained. Also, the results of these experiments and the impacts of different distraction factors on drivers' physiological responses, visual signals, or their performances are categorized and described. Furthermore, this study discusses the factors of the existing methodologies and their results, along with pointing out the research gaps. The purpose of this study is to assist future research and investigation in this field, by creating a review that comprehensively covers different aspects of existing studies and discusses and assesses their methodologies and findings.

1. Introduction

For decades, road safety has been a concern for society. This concern exists because road safety can have major social and economic impacts [1]. According to a report launched by the World Health Organization (WHO) in 2018 [2], in a year, there were more than 1.3 million recorded road deaths as a result of traffic crashes. It has been documented that road traffic injuries are the leading causes of death in the age group of 5 to 29 worldwide [3, 4]. Also, the WHO [2] has reported between 20 and 50 million non-fatal injury cases annually because of road crashes. In addition to the data concerning the effects of car accidents on human life and well-being, there are also significant economic consequences associated with road safety. It is well acknowledged that there is a significant negative influence of increasing trends of road crashes on the economic growth and expenditure of a country [5–11]. Furthermore, according to a study conducted by Chen et al. [12], it is estimated that road injuries will cost the world economy US$1.8 trillion in a 15-year period. Therefore, it is paramount to improve road safety by acquiring information regarding the causes of road crashes and potentially developing methods to minimize them. It has been determined that driver distraction (DD) is a major factor that deteriorates road safety [13, 14]. DD can be defined as engagement with activities or tasks that would divert the drivers' attention away from what is required for safe driving [15].

With the development and deployment of level 2 automated driving systems (ADSs) [16], the role of the driver is becoming central in supervising such systems, and such technologies require constant driver attention [17]. The role of the driver as a safety backup remains crucial, even with the approval of level 3 ADS for Honda in Japan and Mercedes in Germany. The vehicles with National Highway Traffic Safety Administration (NHTSA) level 2 and 3 automation capabilities, in which vehicles have authority over the function of primary control, require drivers' supervision and intervention [18, 19]. While there are techniques such as the platoon strategy that can assist with the improvement of traffic safety [20, 21], it is essential to acknowledge the importance of driver's availability to take over the control of the driving task. Based on protocols developed by NCAP, Europe is to enforce the requirement for driver monitoring systems in vehicles equipped with automated capabilities [17, 22]. Therefore, it could be claimed that with the development of ADS, and the importance of drivers' attention in the utilization of this technology, DD could be a threat to its function.

This review has explored studies [23–35] that have focused on the causes of DD and the development of methods to detect them. To achieve this, most of these studies have conducted experiments, which aim to evaluate the influence of one or several distractions on a driver and/or their driving performance. Such studies have laid the foundation for future research and further investigation into the real-time processing of DD. Additionally, there are existing studies that have conducted reviews on the existing research in this field [23–35]. While acknowledging the contribution of these review studies in furthering the research of DD detection, this study expands on the review of conducted research in this field. The mentioned review studies have not considered all aspects of the existing methodologies or findings. For instance, some have focused on one specific distracting factor such as mobile phones or one category of distracting factors such as external visual distractions [29, 31], while some have not covered the utilization of AI-based methods [26] for data analysis or only considering a specific demographic [32]. This study aims to review the existing studies on DD detection and to find the research gaps, either in methodologies or findings, of the existing studies. Also, this review presents a more comprehensive understanding of the influence of different distracting factors on drivers' physiological reaction, visual signals, and their driving performance.

In the existing methodologies and experiment setups section (Section 2), the distraction factors, the environments that these experiments are conducted in, and methods of data collection and analysis are identified, categorized, and described. Results of the existing studies section (Section 3) include the impacts that distractions have on drivers' physiological and visual signals and their driving performance measures. In the discussion section (Section 4), aspects of the methodologies utilized in the existing research and their findings are described and their gaps are discussed. In the final section of this review, its conclusion is presented.

The following are the main objectives of this review:

(1) Identify the different experimental methodologies that have been employed to investigate DD (Section 2).

(2) Identify the outcomes of the studies in this field (Section 3).

(3) Discuss these methodologies and results and point out the potential gaps in this research (Section 4)

2. Components Incorporated within Methodologies of Existing Studies

This section provides a comprehensive review of the methodologies and procedures utilized in the examined studies to accomplish their objectives, which involve the detection of DD and/or the assessment of its impact. The characteristics of these studies are influenced by several critical elements, including factors that may cause distractions, the experimental setting, the methodologies and instruments employed for data collection, and the approach used to analyze the data, ultimately leading to the attainment of experimental outcomes.

2.1. Applied Distracting Factors. There are many factors that could be classified as distracting. In fact, any engagement to a secondary task, that would divert attention from driving, could be considered as a driving distraction [15]. Therefore, activities such as using a mobile phone, eating, or having a conversation [36–40] could ultimately be distractions to a driver. For example, the distracting factor in a study by Hosking et al. [39] was using a cell phone for sending and receiving text messages, while in another study by Cassidy and MacDonald [41], listening to music was the distracting factor. There are a variety of ways to categorize these distractions. For instance, according to Lee et al. [15], distractions can be classified by their sources, which consist of an object, person, event, and activity. Another study conducted by Pettitt et al. [42] provided a more comprehensive list of distraction factors and categorized them into 3 groups: external sources, internal sources (technology-based), and internal sources (non-technology-based). Young and Lenné [43] provided a list of individual risky activities without categorizing them. Given that there are a variety of specific distracting factors that have been implemented in the reviewed studies' experiments, it is essential that they are categorized to make the identification and comparison of studies and their outcomes possible. The categories introduced in this review paper, as included in Table 1, include hands-free cell phone, hand-held cell phone, texting, conversation, cognitive distractions, music, clothing, hair or makeup, entertainment or information systems, auditory distractions, eating or drinking, passenger-related distractions, reaching or turning, and other visual or external distractions. The distraction factors were categorized as such, to create a sufficiently descriptive distinction in the methodologies of each study (see Figure 1).

2.2. Experiment Environments. There are two major types of classifications for the environments of experiments in this field: real and simulated. The real data are the data gathered in real-life settings using a real vehicle, and the virtual data are gathered when a simulation is set as the experiment environment. Each of these settings offers specific advantages. It is argued that the experiments performed in real-life settings are more reliable as they include more natural conditions [26, 86]. However, simulators can create environments to gather data on isolated and repeatable

Table 1: Categories of elements of the methodology and the outcome of the reviewed studies.

Reference #	Experiment environment		Distracting factor													Distraction detection														Analysis method	
																Driving performance measures							Physiological data								
	Real-life settings	Simulators	Hands-free cell phone	Hand-held cell phone	Texting	Conversation	Cognitive	Music	Clothing, hair, or makeup	GPS, radio, or music player (manual and visual)	Auditory	Eating or drinking	Passenger related	Reaching or turning	Other visual/ external distractions	Brake response/ brake force/ response time	Speed	Lane position/ lateral control	Steering	Headway/ longitudinal control	Accident probability/ error rate	Acceleration and throttle	Heart rate	Brain activity/ mental workload	Breathing rate	Skin conductivity/ perspiration	Body/ head position/ movement	Eye movement/ pupil size/ blinking	Questionnaire	Artificial intelligence-based methods	Conventional data analysis
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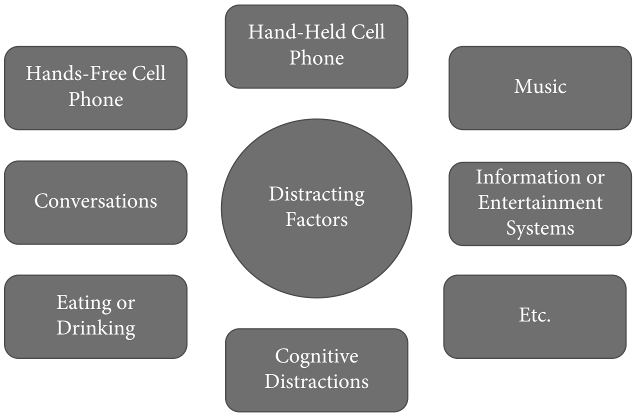

Figure 1: Distracting factors associated with DD.

conditions and mitigate the risks of real-life setting experiments [96]. In this study, we classified the experimental environments into two groups: real-life settings and simulation-based settings (see Figure 2).

2.2.1. Real-Life Settings. Some studies design their experiments to take place in real-life settings [46, 49–51, 55, 97]. This is where the experiment participants either drive their own vehicles or a vehicle provided to them to perform their daily life driving or perform specific driving scenarios. Most studies in this field have their unique definition of their experiment environments. One major distinction that could be pointed out between how studies have defined their experiment environments under this category is if the routes and the scenarios of the experiments are predetermined. To clarify, some studies do not have predetermined scenarios and encourage the participants to drive their vehicles as they normally do [98], while some studies have more defined and predetermined environments, such as test tracks and closed roads.

(1) Open Road and Naturalistic Settings. As mentioned above, some experiments choose open roads or naturalistic settings as their experiment environment. For example, in studies conducted by Foss and Goodwin [60] and Campbell [99], acquisition systems, such as sensors and cameras, were installed in participants' personal vehicles in order to collect data on their daily driving behavior. However, it may be ethically questionable to purposely equip vehicles to capture DD, given the impact on road safety. Given that it has been shown that the recent deployment of detection cameras has reduced the number of mobile phone and seat belt violations [100], it could be surmised that when drivers are being observed, their driving behavior could change.

(2) Closed Roads and Test Tracks. Some studies in the field of DD chose closed roads or test tracks as their experiment environment. For instance, in a study carried out by Owens et al. [51], data collection tools were implemented in a Ford Contour, and participants were to drive in a 1.4 mile-long section of a closed two-lane road. In another study by Ranney et al. [101], their experiment on DD was conducted

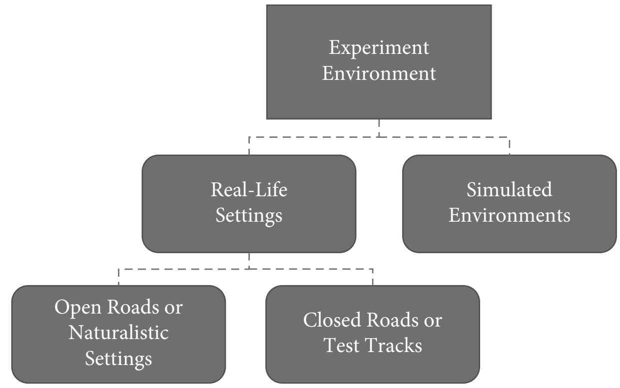

Figure 2: Different environments in DD experiments.

on a three-lane high-speed test track located in Ohio. It can be argued that in these studies, there is more control over the conditions of the experiment and there are fewer risks associated with the experiment, when compared with experiments conducted on open roads and in naturalistic settings.

2.2.2. Simulation. Driving simulators are becoming more popular to be used instead of real-life setting experiments for analyzing driving behavior and distraction factors [78, 82, 84, 85, 88, 89]. They are cost-effective tools that can replicate a real-life driving environment [102, 103]. In addition, using simulators minimizes the risks associated with these studies and allows researchers to create a variety of driving and road conditions, which makes them more desirable than the traditional experiment environments. For instance, a study utilized a static simulator in the Texas A&M University's Transportation Institute to collect their desired data on a simulated four-lane highway [82]. In an experiment carried out by Ahangari et al. [88], simulations of six different road conditions were used to gather the participants' driving performance data. Also, to be able to replicate a more realistic sense of driving, some studies have used motion simulators in their experiment setup [104, 105]. Motion simulators are able to regenerate motion cues of a simulated vehicle to deliver a realistic driving experience [106]. It can be argued that, in the absence of realistic driving experience, driving behavior can be affected negatively and the participants might not be able to respond to the required tasks accurately. An example of this is an experiment conducted by Horberry et al. [45], where a motion platform was used to evaluate the impact of hands-free and in-car entertainment systems on drivers' performance.

2.3. Data Collection Methods. There are different methods of data collection that have been utilized in the previewed studies. Most studies use unique datasets that are collected in their experiments. This could be achieved by utilizing sensors, extracting data from simulators, or gathering subjective information by questionnaires. Some studies analyze datasets that are collected from previous studies or other resources. The following are some of the more common methods of data collection used in previous studies (see Figure 3).

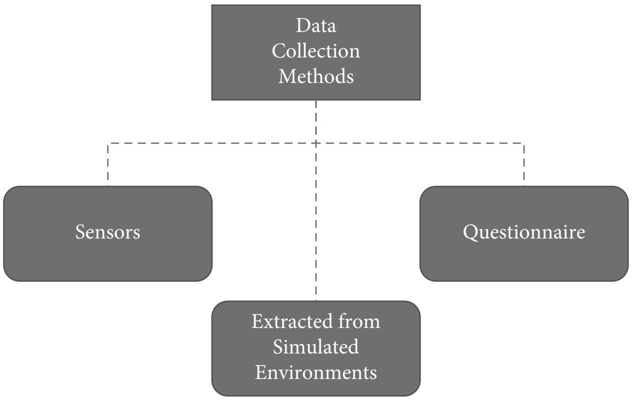

Figure 3: Methods of data collection in studies on DD.

2.3.1. Sensors. There are a variety of sensors that can be used for the detection of DD. This could be through collecting data on performance measures. For instance, one of the sensors that have been used is a smartphone's accelerometer, gyroscope, and magnetometer to acquire performance measure data [73, 79, 86]. Also, brake and pedal pressure could be collected by sensors connected to the pedals [57, 86, 107]. Furthermore, sensors could be used for the collection of participants' physiological data. An example of that is the implementation of electroencephalography (EEG) and electrocardiogram (ECG) sensors in an experiment to gather data regarding the brain activity and heartbeats of the participants [44, 69, 83, 89, 108–110]. Also, functional near-infrared spectroscopy (fNIRS) sensors, which determine the active parts of the cerebral cortex, can be used to monitor drivers' state of alertness [111]. Different cameras have been utilized to detect visual features that could assist in detecting DD [51, 87]. These visual features are a series of images capturing the position of participants' bodies, heads, or eyes or recording their movements [46, 57]. To detect certain body positions, which represent specific distractions, such as using a mobile phone, adjusting the radio, or drinking and eating, a study has used image analysis by utilizing cameras as the sole method of data collection [87]. Another study conducted by Rao et al. [91] used a set of images of drivers safe-driving or distracted, provided by State Farm Insurance Company of the United States, to construct a multilayer convolutional neural network (CNN) mode to detect DD. Also, studies have utilized the "FaceLAB" or other eye-tracking devices to collect eye behavior data that would indicate visual engagements with distractions [39, 53, 66, 68, 69, 83, 89, 112–114].

2.3.2. Extracted from Driving Simulation Software. Another common method to collect data is the extraction of performance measure data from simulation environments of simulators. For example, studies extracted driving performance measures, such as speed, acceleration, throttle, the angular velocity of the steering wheel, the lateral and longitudinal position, time spent and distance traveled veering outside the lane, number of undesired lane crossings, and number of collisions during experiments' simulation, from simulated vehicle dynamic environment [39, 41, 45, 47, 48, 53, 59, 61–67, 70, 71, 74–76, 78, 81, 84, 88].

2.3.3. Questionnaire. Questionnaires are used in some of the conducted studies as a method of gathering subjective data for classification and detecting distraction [41, 55, 62, 75, 77, 115]. A multidimensional workload measure called Driving Activity Load Index (DALI) has been developed and used to evaluate participants' mental load while distracted [58, 116]. The Driver Behavior Questionnaire (DBQ) is another applied questionnaire to collect data from participants' traffic violations, errors, and other aberrant driver behaviors [75, 117].

2.4. Data Analysis Methods. Data analysis is an important aspect of each of the conducted studies in the field of DD detection. To classify the methods of data analysis in this review study, they are divided into two general categories where either artificial intelligence (e.g., machine learning) or conventional data analysis methods are implemented (see Figure 4).

2.4.1. Conventional Data Analysis. There are conventional approaches of data analysis that have been used for a variety of quantifiable datasets in studies conducted in the field of DD detection [76, 77, 81, 83, 89, 90]. For example, a study implemented an analysis of variance (ANOVA) test to investigate changes in eye movements of drivers under different conditions [114]. There are other examples of conventional data analysis, which were used to assess the impact of different distracting factors on driving performance, such as linear regression [64] and *t*-tests [90]. For better understanding the topic of DD and its detection, there are many factors and variables that should be considered, so a complex model would be required for the analysis of collected data. Therefore, it can be argued that conventional methods of data analysis are not ideal for this purpose and for providing accurate outcomes. This might be the reason that AI-based methods of data analysis are being used more often in recent studies in this field.

2.4.2. Artificial Intelligence-Based Methods. With the current advances in the field of artificial intelligence, machine learning-based methods are becoming more desirable to implement when data analysis is required [78, 85–88, 91, 118, 119]. This is because utilizing these algorithms will allow the analysis of data that are difficult to interpret, potentially improve the accuracy and efficiency of the analysis, and give access to real-time feedback of the implemented DD detection systems [120–122]. There are a variety of machine learning methods that have been used for the analysis of experimental data in DD detection. Studies found that support vector machine (SVM) can help in detecting DD with high accuracy by analyzing drivers' performance measures, physiological or visual data [46, 53, 73, 88]. In a study conducted by Ahangari et al. [78], a Bayesian network was implemented to predict DD by using

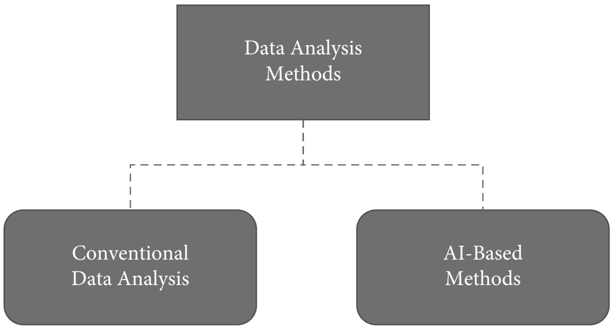

Figure 4: Methods of data analysis in studies on DD.

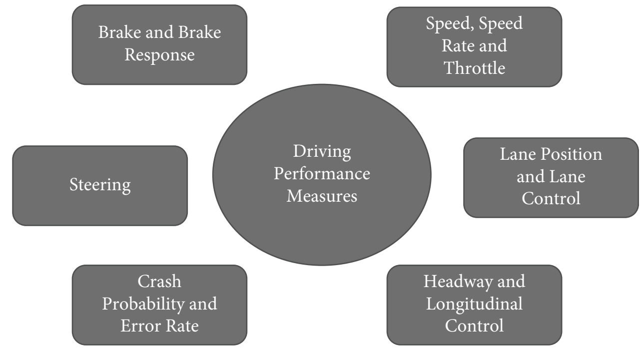

Figure 5: Investigated performance measures in DD studies.

some of the participants' driving performance measures. Also, in one study, as the created dataset included visual information and images, a two-stream deep CNN was applied to analyze the data and accurately detect manual distractions [87]. Despite machine learning being considered an improvement over the conventional methods of data analysis, the effectiveness and accuracy of machine learning-based methods will depend on the nature of the data and the sample size provided [123]. Therefore, some studies have compared different machine learning models to discover the best performing one based on their datasets [80, 82]. In an experiment conducted by McDonald et al. [82], seven different machine learning approaches were compared for a dataset consisting of physiological signals and performance measures. It was concluded that the random forest algorithm is the most desirable option as it had the best performance and accuracy for that dataset [82, 124]. In another study, seven classical machine learning algorithms and seven end-to-end deep learning algorithms were used and compared to detect DD by its participants' physiological and visual signals [80]. This study concluded that a classical machine learning algorithm, which was extreme gradient boosting (XGB), had the best performance amongst the compared methods [80].

3. Results of the Existing Studies

The results of the studies reviewed in this paper focused on the influence of different distraction factors on drivers or their driving performance. For this, the impact of these factors is classified in driving performance measures and drivers' physiological and visual signals. The following subsections describe the findings of reviewed studies regarding these classifications in detail.

3.1. Driving Performance Measures. Driving performance measures are data that are not directly collected from the driver, but rather their performance and data relating to the vehicle. In this subsection, the brake and steering behavior, throttle, vehicle speed and acceleration, lateral and longitudinal control, and crash and error possibility are discussed (see Figure 5).

3.1.1. Brake and Brake Response. As braking and brake responses are important aspects of driving performance and the prevention of crashes, it can be concluded that it is essential to have a comprehensive understanding of the impact of distractions on them. To do so, some research studies focus on or incorporate these measures in their studies on DD detection. Several performance measures that are studied in the reviewed research papers are categorized under "brake/brake response." One of the factors in this category of performance measures is the brake response time. Studies have found that brake responses were slower when there were auditory distractions in the vehicle [54, 69]. Another measure covered in this category is the force applied to the brake pedal [54]. Collecting data regarding this measure could help predict the urgency of the brake response. For example, a study used this measure to develop a system for the detection of distractions during driving [82]. In addition, a study with the primary focus on brake response has concluded that drivers distracted by mobile phones tend to reduce their initial speed with a delay and brake more aggressively when there is a need for deceleration, compensating for this delay [63]. Other studies have investigated the correlation between distractions, such as hand-held/hands-free phone use, texting, and other visual, manual, and cognitive distractions, and brake response, with similar findings [48, 49, 62, 63, 73, 76, 88, 125]. It has been found that this effect worsens during night time [49]. Some studies have found listening to music while driving does not influence the brake response or response time [126]. Lastly, this performance measure has been used to develop machine learning models to detect distracted drivers [57, 59, 78].

3.1.2. Speed, Speed Rate, and Throttle. Vehicle speed is another performance measure that has been widely studied when it comes to its correlation with DD. Vehicle velocity and the ability of the driver to control it are crucial in road safety and hazard management [127, 128]. Thus, many studies compare the average increase or decrease in vehicle speed, as well as speed fluctuations and variations. It has been found that when drivers are distracted by secondary tasks, such as phone use and texting, they lower their speeds to compensate for their distraction [45, 48, 50, 52, 62, 63, 71, 75, 77, 84, 89, 90, 129]. One study claimed that being distracted by clothing, eating, or drinking causes drivers to drive slower when compared to no cell phone, hands-free call, hand-held call, voice command text, and texting conditions [84]. Furthermore, according to studies, the vehicle speed of a distracted driver is dependent on different factors [84, 88]. For example, a study found that when drivers are distracted (by hand-held/hands-free phone, texting, the infotainment system, or clothing and eating) in rural roads with low traffic flow, drivers tend to drive over the speed limit [88]. Also, studies have found that listening to music could influence this performance measure [41, 55]. However, a study has found that there is no significant correlation between this form of distraction and driving speed [44]. Moreover, a research study found that some distraction factors including phone conversation, texting, engagement with music player, and listening to music will create an increase in the speed fluctuations or reduce speed control [74, 81, 82]. On the other hand, based on another research, listening to subjectively interesting audio could reduce the variance in vehicle speed [69]. Furthermore, vehicle speed, its rate of change, and throttle have been used as input elements of machine learning models to detect DD [53, 57, 59, 78, 79, 86, 88].

3.1.3. Lane Position and Lateral Control. Lane positioning and lateral control are considered another important category of performance measures that are affected by DD. In some studies in this field, it is mentioned that distractions can cause a higher level of lateral deviation from the intended lateral position, which is usually the center of road lanes and could be linked to a higher level of crash risk [81]. For instance, in some studies, the standard deviation of vehicle's lane positions in baseline (non-distracted) and distracted conditions was measured and it was found that these values are higher when drivers are distracted by listening to subjectively interesting audio, texting, phone conversations, or visual distractions [39, 47, 48, 61, 67, 69, 70, 75, 89]. Another study concluded that visual distractions' effect on lane positioning depends on the gaze direction and manual interference. This shows that if the driver is gazing away from the road due to the distraction, and when they engage in a manual task, they change lane positioning more frequently [66]. Also, it has been found that conversation, texting, operating the music player, and listening to music during driving activities can increase the standard deviation of the lane position. Another related factor evaluated in studies in this field includes undesired lane crossings. Some research studies have claimed that there are no significant impacts on this factor when drivers listen to music and use hand-held or hands-free phones [44, 56]. However, some studies have found more lane departures when there is engagement with secondary tasks such as texting and phone conversation [64, 65, 74, 75]. Some other studies have stated that the impact of texting on this factor, undesired lane departures, is more apparent if the duration of this task is longer, or if the driver is older than 60 years old [64, 75]. Also, some studies have used lane positioning behavior to define abnormal or distracted driving behavior or create a model to detect distracted driving [59, 73, 78, 82].

3.1.4. Steering. Steering behavior is another key category of performance measures that can be accounted for as the outcome of being distracted while driving. One factor that would be under this is the variation in steering wheel angle. Some studies have found that the standard deviation of the steering wheel angle would be higher if the driver is distracted by phone conversations and manual distractions such as music player, texting, or listening to music [51, 67, 70, 81]. It should be noted that it has been found that some forms of distraction, such as texting, have a higher effect on variation in steering wheel angle, and some, such as listening to music, have a lower influence on this factor [70, 81]. In addition, it has been claimed that in the younger and the male demographics, the variation of steering wheel angles is impacted less by distractions, when compared to other demographics [70, 81]. Another factor that could be used to detect distraction is the quantity of statistically large steering corrections or steering wheel reversal rate, which is normally caused by compensation for unintended or undesired lateral positions. Research studies have found that when drivers are distracted by secondary tasks, they will have more steering wheel corrections [66, 70]. The intensity of this factor, the steering wheel correction, is dependent on the type of distraction. A study finds that non-visual distractions cause smaller steering wheel reversal rates than visual tasks [66]. Moreover, it is found that the maximum steering wheel velocity and its standard deviation can be influenced by distractions. Some research studies also conclude that texting while driving increases the maximum steering wheel velocity and its standard deviation [51, 75]. Also, in conducted studies, steering performance factor data have been used to develop machine learning models to detect distraction in drivers [53, 57, 59, 79, 86].

3.1.5. Headway and Longitudinal Control. Headway or the distance between the subject vehicles and the vehicles in front of them could be of interest in studying DD. Some studies have measured this distance or the headway time and compared baseline conditions with distracted ones [50, 81]. Research studies have found that when drivers are distracted by a mobile phone conversation, texting, manual distractions (infotainment systems), or auditory distractions (audio or music), they leave more space between their vehicles and the vehicles in front [39, 47–50, 56, 67, 69, 76, 81]. Some studies suggested that younger and male participants' headway distance, in their experiments, was less influenced by distractions, such as texting [61, 81]. Also, it has been concluded that this impact becomes more severe during nighttime [49]. However, there are claims that hands-free phone conversations do not affect this performance measure [56]. Furthermore, this performance measure has been used for the development of a machine learning model to detect visual and cognitive distractions [59, 82].

3.1.6. Crash Probability and Error Rate. The crash probability and error rate of drivers could be another driving performance measure that is evaluated for the detection of driving distractions. One study found that on rural roads, the chance of collision during an interruption, such as animal passing, becomes higher; also, on freeways, the probability of crashes with other cars moving at the expected velocity increases, when the driver is distracted by phone, texting, or manual distractions [88]. Other studies have found that when the participants were distracted by music, especially high arousal music, the number of collisions, unintended lane crossings, and disregarded red traffic lights rises [41, 44]. Another study concluded that phone conversations, texting, using the music player, and listening to music cause driving performance degradation which leads to a higher risk of car crashes [81]. Moreover, it has been shown that using handheld phones and texting can considerably increase the risk of crashes, while hands-free phones do not have this impact [56, 60, 62, 64, 71, 75, 76, 129]. It has been argued that while distracted by texting, older drivers have a higher probability of crashes [75]. Also, these distractions would increase the chances of mistakes in navigation and following driving instructions [47]. Moreover, the probability of crashes for distracted driving has been a factor used for developing a machine learning method to detect driving distraction [78].

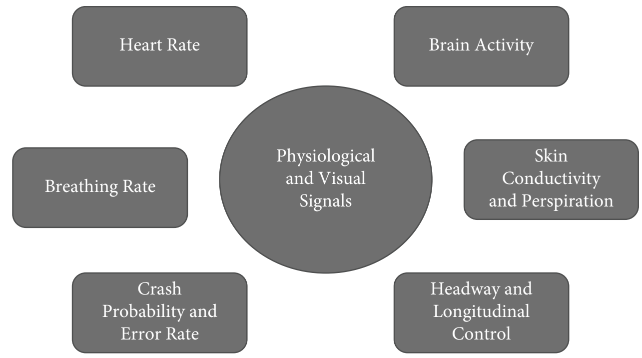

Figure 6: Investigated physiological responses in DD studies.

3.2. Drivers' Physiological and Visual Signals. Drivers' physiological and visual data can be impacted by distractions based on the results of the previous studies [46, 89, 113, 130–132]. The physiological data are data directly gathered from the drivers' bodies such as heart rate, brain activity, breathing rate, skin temperature, and eye movement. The visual data refer to collected information relating to the position or movement of different body parts of the drivers. These studies either discuss the quantifiable changes observed in these physiological and visual signals or use these data for the development of distraction detection methods (see Figure 6).

3.2.1. Heart Rate. One of the physiological signals that have been used for the detection of distracted drivers is their heart rate. This is because short-term heart rate variability could reflect the cognitive workload of a driver [130]. Studies have found that visual and cognitive distraction can cause an elevated heart rate in a driver [52, 89]. The rate of this elevation is dependent on the complexity and the engagement level of the distractor [89]. Also, a study has found that the effect of cognitive distraction on heart rate is more severe in young drivers and not considerable in middle-aged drivers [52]. According to a study, there is not a measurable difference between the heart rate of a driver listening to music or subjectively interesting or uninteresting audio or one not listening to any audio [44, 69]. However, this physiological signal has been used to develop a machine learning model for the detection of driving distraction by texting or having a conversation [82].

3.2.2. Brain Activity. It has been found that it is possible to detect changes to brain activity while performing specific tasks during driving [131]. Therefore, brain activity and mental workload are other physiological signals that can be evaluated to detect distraction in drivers. Studies have observed that when drivers are distracted by cognitive distractions, there will be a higher brain activity in their frontal lobe based on EEG band readings [93, 133, 134]. Another study found that brain activity, or to be more specific, alpha spindles rate, increases when drivers are distracted by an auditory distraction [135]. Also, a study implemented a series of questionnaires to collect subjective ratings of the mental load of the participants and used this information to detect DD [58].

3.2.3. Breathing Rate. Breathing rate is another physiological signal that could be used for the detection of DD. It has been found that performing highly demanding mental tasks causes a higher respiratory rate [136]. As mentioned in the previous subsection, driving distractions could lead to elevated mental workload. Therefore, data regarding a driver's breathing rate could be used for the detection of DD. Also, this kind of physiological data has been used for the development of a machine learning model to detect distracted drivers [82, 132].

3.2.4. Skin Conductivity and Perspiration. Measuring skin conductivity, which is directly related to perspiration, is another method that has been used for the detection of distracted drivers. It has been found that skin conductivity increases when drivers are distracted by visual and auditory distractions [89]. Studies have used the palm electrodermal activity and nasal electrodermal activity to measure skin conductance response and used the collected data to develop machine learning methods or other statistical methods to detect distraction, such as cognitive distractions and texting activities while driving [65, 80, 82].

3.2.5. Body and Head Movement. Another method for detecting distraction in drivers could be studying body or head positions and movements. According to a study, head position data, or to be more specific the pitch and yaw of the driver's head, could be used to indicate the driver's field of view and focus of attention [46]. This information could be used for the detection of diverted vision of drivers. Some studies use drivers' body or head positions, which are usually measured by cameras and image analysis using machine learning methods, to detect different DD conditions such as using the phone, texting, engaging with the infotainment systems, reaching or turning, eating and drinking, doing makeup, and talking with passengers [57, 59, 68, 72, 85, 87, 92, 95].

3.2.6. Eye Movement/Pupil Size/Blinking. This category of physiological signals is a commonly used set of information utilized to detect driving distractions. One factor in this category is the vision focus. A study has found that when drivers are engaged with hand-held or hands-free smartphones, they lose some peripheral vision or exhibit tunnel vision [113]. Furthermore, based on some other conducted studies, distractions, such as specific tasks during phone use and other manual and visual distractions, would cause longer and a higher number of off-road glances [39, 51, 56, 66, 83, 89, 94]. It has been found that this effect is more prevalent in younger drivers [60]. However, one study has claimed that cognitive distractions can cause drivers to be more focused on the center of the road, when compared to the not distracted condition [89]. Moreover, pupil diameter is another factor under this category that has been considered as a physiological signal that could assist with the prediction of distraction during driving activities. A study has reported that the diameter of the driver's pupil will have a slight decrease on average and a considerably lower standard deviation with the existence of audio distractions [69]. In addition, it has been found that hand-held and hands-free phones could increase the frequency of blinking during a driving task of taking over a car in front [114]. In general, eye-tracking data have been used to develop a machine learning model to detect distractions while driving [57, 68, 80].

4. Discussion

In this section, the reviewed studies are assessed, and the research gaps associated with them are discussed. Table 1 has been created to build a more comprehensive understanding of each element of the methodology and results of the studies that are reviewed. As illustrated, different aspects of the methodologies and the outcomes of the reviewed research papers are categorized. In Table 1, the experiment environments, distracting factors, analysis method, and the method of distraction detection are classified. This table visualizes the work done in this field. In this review, the methodologies and experiment setups of the reviewed studies are discussed in detail. These factors have been reviewed and described to assist future research and to create a clear image of the existing methods regarding the research in the field of DD detection. Based on the objectives of research or the availability of tools and technology, these methodologies could be selected for the related studies.

The distracting factors considered are a major element of the reviewed studies. In some of the studies discussed above, it has been pointed out that different distracting factors will have an impact on the intensity of distraction and subsequently on the drivers' performance [56, 60, 62, 64–66, 71, 74–76, 129]. It could be argued that to have a comprehensive research experiment, the influence of several distracting factors and their intensity that cause different types of distractions, such as visual, cognitive, auditory, and manual, are studied and analyzed. As discussed in Subsection 2.2, while there are advantages of real-life setting experiment environments, simulators can simplify research by mitigating most risks that are associated with a driving experiment and allow scholars to research on specific scenarios or study the impact of a specific factor. Therefore, it could be claimed that they would be more desirable to be utilized as the experiment environment [96]. Also, the use of driving simulators has allowed the researchers to widen the type of experiments they can explore in a safer environment as well as to retrieve performance measure data from these simulators. It should be noted that utilizing a motion platform could increase the complexity of experiments because if the visual and motion cues of the simulation do not fully match, they can cause motion sickness [137]. However, they are capable of creating a more realistic experience for the participants and therefore bring out natural reactions from experiment participants [138]. In addition, using simulators, researchers will have more control over the types of scenarios, weather conditions, types of terrains, traffic conditions, etc. This can be quite important as it has been shown that conditions such as extreme weather can influence the risks associated with driving and performance measures [139, 140].

As mentioned in Subsection 2.3, there are several methods to collect data for the conducted experiments. It is important that the validity and accuracy of the collected data are considered. For example, questionnaires could be informative measures, but they are subjective and could create uncertainty in the validity of the gathered data [141, 142]. On the other hand, certain questionnaires, such as the Susceptibility to Driver Distraction Questionnaire (SDDQ), which are developed to better understand driver distractions, are shown to be relatively reliable for the purpose, while providing important data to the scholars [143]. Also, implementing sensors is a common method to gather a variety of data. With the use of current technology, it has become easier to collect data regarding the physiological signals of experiment participants. For instance, EEG signals have been utilized to monitor the rates of participants' brain activity and the level of attention [144]. However, they are likely to be influenced by participants' muscular activities or heartbeat, which will lead to inaccurate readings of EEGs [145]. Therefore, it is important when using sensors that their accuracy and potential error in the data they provide are considered and assessed.

Furthermore, as it has been previously mentioned, a method of data analysis for many of the reviewed studies is the artificial intelligence-based analysis method. As shown in Table 1, the AI-based methods are becoming increasingly popular for certain datasets related to DD. While the utilization of AI-based models might be preferred to the conventional data analysis methods, each of these models has its pros and cons and is suitable for certain types of datasets. For example, support vector machine (SVM) algorithms have been used for DD detection by performance measure, physiological and visual data [46, 53, 73, 88]. It has been claimed that this method of machine learning is not ideal for large datasets as it has a high training time, it is sensitive to unscaled data, and it does not perform well when there is a high level of noise in the data [82, 146–148]. Another machine learning algorithm that has been used in the existing studies in this field is random forest (RF) [82, 124]. While in these cases, this algorithm was more accurate in prediction of DD than SVM algorithms, it has been claimed that the disadvantages of using this algorithm include inaccuracy when used for regressions, being slow due to its complexity, lack of control or knowledge on what the model does, and instability and sampling errors [82, 146, 148–150]. Another study compared several classical machine learning and end-to-end deep learning methods, including random forest (RF), extreme gradient boosting (XGB), long short-term memory (LSTM) network, and spectro-temporal ResNet (STRNet), for the detection of DD by physiological and visual signals. This study concluded that the XGB algorithm was more accurate than RF and the other algorithms for its data analysis purposes [80]. This algorithm has been shown to be accurate and efficient [151–153]; however, it could be claimed that it has a relatively higher risk of overfitting than some of the other algorithms [153]. Furthermore, in recent years, studies have commonly used deep learning algorithms, such as convolutional neural network or LSTM network, for image classification and detection of specific distraction factors [72, 80, 85, 154–159]. It should be pointed out that deep learning models are generally intensive computational models, which require a large, clean, and well-structured data sample [160]. Therefore, it is important to recognize that even if one machine learning algorithm performs well for one dataset, it might not be ideal to use it in another experiment. Also, the field of artificial intelligence is constantly growing and improving. Therefore, it can be argued that the accuracy and efficiency of AI-based models could improve further. The field of artificial intelligence (AI) is constantly evolving and advancing, and there are many exciting future works that could be conducted. One important area of focus will be on developing AI systems that are more transparent and explainable, so that users can understand how they make decisions and trust their outputs [161]. Another challenge will be to continue improving AI algorithms and models to make them more accurate and efficient, while also addressing issues of bias and fairness [162]. Additionally, as AI becomes more ubiquitous in our daily lives, there will be a need to ensure that ethical considerations are incorporated into the development and deployment of these systems [163]. Overall, the future of AI in DD detection is promising, but there are also many important challenges that must be addressed to ensure its beneficial use.

The impacts of distractions on drivers' performance measures have been comprehensively researched. There is a clear agreement that the brake responses are delayed when drivers are distracted, especially if the distraction causes the driver to look away from the road. Also, to compensate, drivers tend to reduce their speed while distracted and their headway distance gets influenced. Furthermore, their steering behaviors and lane control responses suffer, as there are more sudden steering and undesired lane positions when they are distracted. Besides, the conducted studies have concluded that the probability of crashes and driving errors increases when drivers are engaged in secondary tasks. Drivers' physiological and visual signals have been utilized to detect distracted drivers in previous studies' experiments. Physiological signals have not been utilized for long, in the field of DD detection, but some of the existing studies have found a direct link between some physiological signals, such as heart rate, brain activity, and skin conductivity, and DD. It has been found that DDs cause the elevation of heart rate, brain activity, and skin conductivity [52, 89, 133, 134]. Also, it has been shown that some driving distractions would decrease the peripheral vision, increase off-road glances, and change pupil diameter. Some other studies have used this information to develop machine learning-based methods to detect distracted drivers [39, 51, 56, 66, 83, 89]. With image analysis and implementation of machine learning techniques, such as neural networks, the visual signals of drivers, which consist of their head and body movements, can be used to monitor DD [72, 80, 154–156].

From Table 1, the following gaps can be found, using the categories described in the flowchart (see Figure 7).

4.1. Experiment

(a) There is a lack of comprehensive research on the influence of distraction on drivers in vehicles with partial, high, or full automation (level 2+ in SAE classification)

While the influence of DD in level 2 automated driving has been investigated [83], there is a gap in the research on DD and its impact on driving in higher levels of vehicle automation.

(b) There are no studies that consider and evaluate the impact of DD based on participants' age and gender while measuring their physiological data, excluding heart rate and eye-tracking data.

While some studies have examined the impacts of DD on different demographics performance measures [45, 61, 64, 70, 75, 81], eye-tracking data [60], or heart rate [52], none have researched its impact on other physiological signals.

(c) There is the absence of examination on the impact of manual distraction such as the use of entertainment or information systems on participants' breathing rate and objective data regarding brain activity.

While some studies have considered the impact of manual distractions on performance measures [45, 59, 61, 77, 81], skin conductivity [89], heart rate [89], and eye-tracking data [51, 57, 83], none have considered other physiological signals.

(d) There are no studies that have extensively investigated the influence of music in general or different genres of music on all drivers' physiological signals.

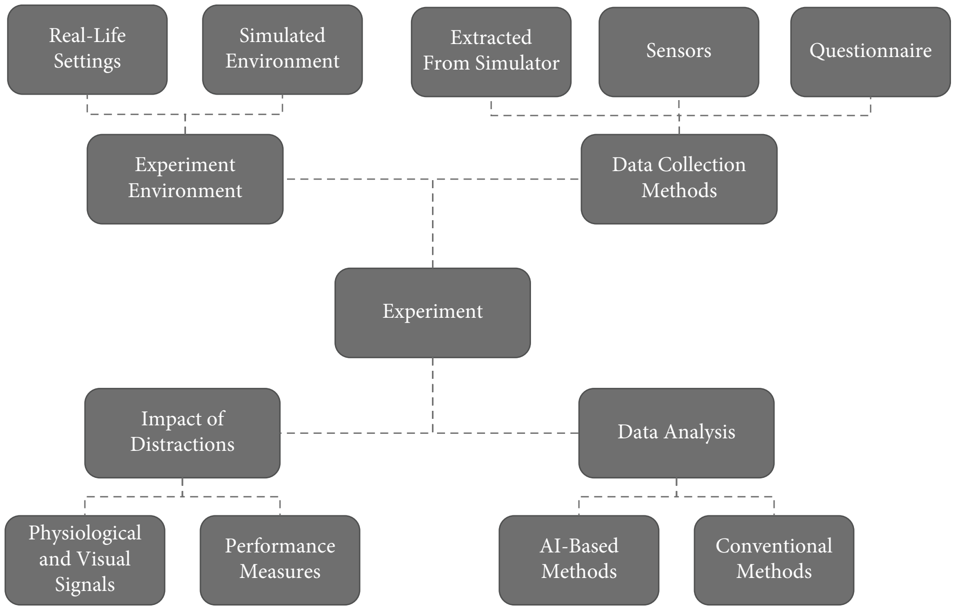

Figure 7: Flowchart for visualization of aspects of experiment design in the field of DD.

While there are studies that have investigated the influence of music or different tempos of music on driving performance [41, 54, 55, 81] or drivers' heart rate [44], none have extensively compared the impact of different genres of music and none have examined their influence on other physiological signals.

4.2. Environment Experiment

(a) In the experiments performed on simulators or in real-life settings, there is a lack of applying a variety of road and weather conditions. For example, the influence that different weather conditions can have on driving distractions is not identified.

While the impact of DD in road types and traffic complexity has been examined [62, 164], other conditions that may influence this have not been investigated.

(b) There are gaps that have not been explored where the experiment setup consists of a motion platform, especially when the impact on the physiological data is considered.

While motion platforms have been used for evaluating the impact of DD on drivers' performance measures [39, 45, 58, 63, 76, 164], the impact on drivers' physiological signals has not been considered when they are utilized.

4.3. Data Collection Methods

(a) There is a lack of study investigating, depending on the type of distraction, which type of signals is more accurate to identify the distraction.

For instance, a study has utilized EEG to evaluate brain activity [135] and another has used a questionnaire for the same purpose [58]. However, there is not a study that has compared the accuracy of the results based on two different methods of data collection.

4.4. Impact of Distraction

(a) There is a lack of comprehensive research on the influence of distracting factors on some of the drivers' physiological signals, such as brain activity and breathing rate.

(b) There are other physiological signals such as muscle activity (EMG), cardiovascular dynamics (BVP), and body temperature that might be impacted by distractions that have not been considered in the reviewed studies.

(c) There is not a comprehensive study that discovers and compares the impact of several different distracting factors on the physiological reaction of drivers.

4.5. Data Analysis

(a) With the improvements that are constantly being made in the field of AI-based algorithms, new models could be used to improve the accuracy and efficiency of data analysis. AI-based methods poorly fused signals from different sources (images being the main sources of data).

5. Conclusion

In this paper, a comprehensive review of existing studies in the field of driver distraction detection was conducted. There are a variety of methodologies and experiment setups that are utilized to investigate driving distractions and their impact on drivers and their driving performance. The elements of methodologies categorized and discussed in this study are distracting factors, experiment environments, data collection, and analysis methods. The review of these elements was conducted to create a general understanding of the tools and methods that have been used in the research of this field. Moreover, an important aspect of these studies is their findings and results. In this study, the results were categorized into performance measures and physiological and visual signals. The reviewed studies aimed to assess the impact of DD on one or more performance measures or physiological and visual signals. By reviewing these results, it is clear that most studies conclude that there is a considerable impact on drivers and their driving performance when they are distracted. Also, the findings suggest that driver distraction is a serious concern for road safety, as it can impair driving performance and cause accidents. Depending on the type of distraction and level of engagement required for the distracting tasks, these measures could be influenced differently. It should be mentioned that there are some differences in the outcome of their experiments that might contradict each other, but the vast majority of them do not have major divergence in their conclusions.

Lastly, in the discussion section of this study, different methodologies and findings of some of the reviewed studies were identified and illustrated in Table 1. This table was made to assist readers with having a general understanding of the state of the art and the areas of interest in this field. Also, in this section of this review study, discussions were created to compare different elements of the existing methodologies. These discussions draw attention to the value of testing a variety of distracting factors, the advantages and disadvantages of different experiment environments and data collection methods, and the importance of selecting the appropriate AI-based methods for data analysis. Furthermore, in the discussion section of this study, it is pointed out that despite minor disagreements between the reviewed studies, it can be concluded that DD has a clear impact on drivers and their driving performance measures. Moreover, some gaps that have not been explored in this field are mentioned to assist further research in this field. The review of the methodologies used in these studies and their findings provide insights into the tools and methods that researchers use to investigate driver distraction, which can help guide future research in this area. Overall, this paper highlights the importance of understanding the impact of driver distraction on driving performance and safety and provides a comprehensive review of the existing literature on this topic.

Data Availability

No underlying data were collected or produced in this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] B. Vanholme, D. Gruyer, B. Lusetti, S. Glaser, and S. Mammar, "Highly automated driving on highways based on legal safety," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 1, pp. 333–347, 2012.

[2] World Health Organization, "Road traffic injuries," 2022, https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries.

[3] World Health Organization, "Global status report on road safety," 2018, https://www.who.int/publications/i/item/9789241565684.

[4] Australian Institute of Health and Welfare, "Deaths in Australia," 2023, https://www.aihw.gov.au/reports/life-expectancy-death/deaths-in-australia.

[5] R. Gorea, "Financial impact of road traffic accidents on the society," *International Journal of Ethics, Trauma and Victimology*, vol. 2, no. 01, pp. 6–9, 2016.

[6] L. B. Connelly and R. Supangan, "The economic costs of road traffic crashes: Australia, states and territories," *Accident Analysis and Prevention*, vol. 38, no. 6, pp. 1087–1093, 2006.

[7] C. Juillard, M. Labinjo, O. Kobusingye, and A. A. Hyder, "Socioeconomic impact of road traffic injuries in West Africa: exploratory data from Nigeria," *Injury Prevention*, vol. 16, no. 6, pp. 389–392, 2010.

[8] O. J. Afolabi and K. Gbadamosi, "Road traffic crashes in Nigeria: causes and consequences," *Transport and Logistics: The International Journal*, vol. 17, no. 42, pp. 2406–1069, 2017.

[9] B. R. Sharma, "Road traffic injuries: a major global public health crisis," *Public Health*, vol. 122, no. 12, pp. 1399–1406, 2008.

[10] M. Heron-Delaney, J. Kenardy, E. Charlton, and Y. Matsuoka, "A systematic review of predictors of post-traumatic stress disorder (PTSD) for adult road traffic crash survivors," *Injury*, vol. 44, no. 11, pp. 1413–1422, 2013.

[11] A. Chandran, G. Kahn, T. Sousa, F. Pechansky, D. M. Bishai, and A. A. Hyder, "Impact of road traffic deaths on expected years of life lost and reduction in life expectancy in Brazil," *Demography*, vol. 50, no. 1, pp. 229–236, 2013.

[12] S. Chen, M. Kuhn, K. Prettner, and D. Bloom, "The global macroeconomic burden of road injuries: estimates and projections for 166 countries," *The Lancet Planetary Health*, vol. 3, no. 9, pp. e390–e398, 2019.

[13] T. A. Dingus, "Driver crash risk factors and prevalence evaluation using naturalistic driving data," *Proceedings of the National Academy of Sciences*, vol. 113, no. 10, pp. 2636–2641, 2016.

[14] O. Oviedo-Trespalacios and M. A. Regan, "Driver distraction," *Transport Sustainability and Health*, vol. 7, pp. 113–120, 2021.

[15] J. D. Lee, K. L. Young, and M. A. Regan, "Defining driver distraction," *Driver distraction: Theory, effects, mitigation*, vol. 13, no. 4, pp. 31–40, 2008.

[16] Sae International, "Taxonomy and definitions for terms related to driving automation systems for on-road motor

vehicles," SAE International, 2021, https://www.sae.org/standards/content/j3016_202104/.

[17] N. C. A. P. Euro, ""Test & assessment protocol," assisted driving, highway assist systems," 2020, https://cdn.euroncap.com/media/58813/euro-ncap-ad-test-and-assessment-protocol-v10.pdf.

[18] S. O. A. E. International, "Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles," *SAE international*, vol. 4970, no. 724, pp. 1–5, 2018.

[19] A. Eriksson and N. A. Stanton, "Takeover time in highly automated vehicles: noncritical transitions to and from manual control," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 59, no. 4, pp. 689–705, 2017.

[20] X. Yang, Y. Zou, and L. Chen, "Operation analysis of freeway mixed traffic flow based on catch-up coordination platoon," *Accident Analysis and Prevention*, vol. 175, Article ID 106780, 2022.

[21] Z. Zhong, E. E. Lee, M. Nejad, and J. Lee, "Influence of CAV clustering strategies on mixed traffic flow characteristics: an analysis of vehicle trajectory data," *Transportation Research Part C: Emerging Technologies*, vol. 115, Article ID 102611, 2020.

[22] The European Parliament And The Council Of The European Union, *Type-approval Requirements for Motor Vehicles and Their Trailers, and Systems, Components and Separate Technical Units: General Safety and the protection of Vehicle Occupants and Vulnerable Road Users*, The European Parliament And The Council Of The European Union, Strasbourg, France, 2022.

[23] J. K. Caird, S. M. Simmons, K. Wiley, K. A. Johnston, and W. J. Horrey, "Does talking on a cell phone, with a passenger, or dialing affect driving performance? An updated systematic review and meta-analysis of experimental studies," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 60, no. 1, pp. 101–133, 2018.

[24] H.-B. Kang, "Various approaches for driver and driving behavior monitoring: a review," in *Proceedings of the IEEE International Conference on Computer Vision Workshops*, pp. 616–623, Sydney, Australia, October 2013.

[25] A. K. Huemer, M. Schumacher, M. Mennecke, and M. Vollrath, "Systematic review of observational studies on secondary task engagement while driving," *Accident Analysis and Prevention*, vol. 119, pp. 225–236, 2018.

[26] P. Papantoniou, E. Papadimitriou, and G. Yannis, "Review of driving performance parameters critical for distracted driving research," *Transportation Research Procedia*, vol. 25, pp. 1796–1805, 2017.

[27] D. W. Eby, *Driver Distraction and Crashes: An Assessment of Crash Databases and Review of the Literature*, University of Michigan Transportation Research Institute, Ann Arbor, MI, USA, 2003.

[28] T. Cvahte Ojsteršek, "Eye tracking use in researching driver distraction: a scientometric and qualitative literature review approach," *Journal of Eye Movement Research*, vol. 12, no. 3, 2019.

[29] A. M. Ali, "Distracted driving using mobile phone," *Anbar Journal of Engineering Sciences*, vol. 9, no. 2, 2021.

[30] D. Stavrinos, C. N. Pope, J. Shen, and D. C. Schwebel, "Distracted walking, bicycling, and driving: systematic review and meta-analysis of mobile technology and youth crash risk," *Child Development*, vol. 89, no. 1, pp. 118–128, 2018.

[31] J. S. Decker, S. J. Stannard, B. McManus, S. M. Wittig, V. P. Sisiopiku, and D. Stavrinos, "The impact of billboards on driver visual behavior: a systematic literature review," *Traffic Injury Prevention*, vol. 16, no. 3, pp. 234–239, 2015.

[32] J. K. Caird and W. J. Horrey, "A review of novice and teen driver distraction," *Handbook of Teen and Novice Drivers*, pp. 189–210, CRC Press, Boca Raton, FL, USA, 2016.

[33] G. Merlhiot and M. Bueno, "How drowsiness and distraction can interfere with take-over performance: a systematic and meta-analysis review," *Accident Analysis and Prevention*, vol. 170, Article ID 106536, 2022.

[34] I. K. Verma and S. Karmakar, "Driver distraction: methodological review," in *Proceedings of the International Conference on Research into Design*, pp. 849–859, Springer, Boston MA USA, December, 2017.

[35] A. Kashevnik, R. Shchedrin, C. Kaiser, and A. Stocker, "Driver distraction detection methods: a literature review and framework," *IEEE Access*, vol. 9, pp. 60063–60076, 2021.

[36] J. C. Stutts, D. W. Reinfurt, L. Staplin, and E. Rodgman, "The role of driver distraction in traffic crashes," *AAA Foundation for Traffic Safety*, vol. 202, 2001.

[37] M. M. Haque, O. Oviedo-Trespalacios, A. K. Debnath, and S. Washington, "Gap acceptance behavior of mobile phone–distracted drivers at roundabouts," *Transportation Research Record*, vol. 2602, no. 1, pp. 43–51, 2016.

[38] I. Donkor, A. Gyedu, A. K. Edusei, B. E. Ebel, and P. Donkor, "Mobile phone use among commercial drivers in Ghana: an important threat to road safety," *Ghana Medical Journal*, vol. 52, no. 3, pp. 122–126, 2018.

[39] S. G. Hosking, K. L. Young, and M. A. Regan, "The effects of text messaging on young drivers," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 51, no. 4, pp. 582–592, 2009.

[40] J. Shi, D. Peng, and Y. Xiao, "Exploration of contributing factors of different distracted driving behaviors," *Promet-Traffic and Transportation*, vol. 31, no. 6, pp. 633–641, 2019.

[41] G. Cassidy and R. MacDonald, "The effects of music choice on task performance: a study of the impact of self-selected and experimenter-selected music on driving game performance and experience," *Musicae Scientiae*, vol. 13, no. 2, pp. 357–386, 2009.

[42] M. Pettitt, G. Burnett, and A. Stevens, "Defining driver distraction," *Intelligent Transportation Society of America-12th World Congress on Intelligent Transport Systems*, vol. 5, 2005.

[43] K. L. Young and M. G. Lenné, "Driver engagement in distracting activities and the strategies used to minimise risk," *Safety Science*, vol. 48, no. 3, pp. 326–332, 2010/03/01/2010.

[44] W. Brodsky, "The effects of music tempo on simulated driving performance and vehicular control," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 4, no. 4, pp. 219–241, 2001.

[45] T. Horberry, J. Anderson, M. A. Regan, T. J. Triggs, and J. Brown, "Driver distraction: the effects of concurrent in-vehicle tasks, road environment complexity and age on driving performance," *Accident Analysis and Prevention*, vol. 38, no. 1, pp. 185–191, 2006.

[46] E. Murphy-Chutorian, A. Doshi, and M. M. Trivedi, "Head pose estimation for driver assistance systems: a robust algorithm and experimental evaluation," in *Proceedings of the 2007 IEEE intelligent transportation systems conference*, pp. 709–714, IEEE, Bellevue, WA, USA, August, 2007.

[47] F. A. Drews, M. Pasupathi, and D. L. Strayer, "Passenger and cell phone conversations in simulated driving," *Journal of*

Experimental Psychology: Applied, vol. 14, no. 4, pp. 392–400, 2008.

[48] F. A. Drews, H. Yazdani, C. N. Godfrey, J. M. Cooper, and D. L. Strayer, "Text messaging during simulated driving," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 51, no. 5, pp. 762–770, 2009.

[49] I. A. Al-Darrab, Z. A. Khan, and S. I. Ishrat, "An experimental study on the effect of mobile phone conversation on drivers' reaction time in braking response," *Journal of Safety Research*, vol. 40, no. 3, pp. 185–189, 2009.

[50] G. Yannis, E. Papadimitriou, X. Karekla, and E. Kontodima, "Mobile phone use by young drivers: effects on traffic speed and headways," *Transportation Planning and Technology*, vol. 33, no. 4, pp. 385–394, 2010.

[51] J. M. Owens, S. B. McLaughlin, and J. Sudweeks, "Driver performance while text messaging using handheld and in-vehicle systems," *Accident Analysis and Prevention*, vol. 43, no. 3, pp. 939–947, 2011.

[52] B. Reimer, B. Mehler, J. F. Coughlin, N. Roy, and J. A. Dusek, "The impact of a naturalistic hands-free cellular phone task on heart rate and simulated driving performance in two age groups," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 14, no. 1, pp. 13–25, 2011.

[53] L. Jin, Q. Niu, H. Hou, H. Xian, Y. Wang, and D. Shi, "Driver cognitive distraction detection using driving performance measures," *Discrete Dynamics in Nature and Society*, vol. 2012, Article ID 432634, 12 pages, 2012.

[54] W. P. Berg and D. J. Dessecker, "Evidence of unconscious motor adaptation to cognitive and auditory distraction," *Adaptive Behavior*, vol. 21, no. 5, pp. 346–355, 2013.

[55] W. Brodsky and Z. Slor, "Background music as a risk factor for distraction among young-novice drivers," *Accident Analysis and Prevention*, vol. 59, pp. 382–393, 2013/10/01/2013.

[56] G. M. Fitch, "The impact of hand-held and hands-free cell phone use on driving performance and safety-critical event risk," Virginia Polytechnic Institute and State University, Blacksburg, VA, USA, DOT HS 811 757, 2013.

[57] N. Li, J. J. Jain, and C. Busso, "Modeling of driver behavior in real world scenarios using multiple noninvasive sensors," *IEEE Transactions on Multimedia*, vol. 15, no. 5, pp. 1213–1225, 2013.

[58] H. Rouzikhah, M. King, and A. Rakotonirainy, "Examining the effects of an eco-driving message on driver distraction," *Accident Analysis and Prevention*, vol. 50, pp. 975–983, 2013/01/01/2013.

[59] F. Tango and M. Botta, "Real-time detection system of driver distraction using machine learning," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 2, pp. 894–905, 2013.

[60] R. D. Foss and A. H. Goodwin, "Distracted driver behaviors and distracting conditions among adolescent drivers: findings from a naturalistic driving study," *Journal of Adolescent Health*, vol. 54, no. 5, pp. S50–S60, 2014.

[61] Y. Peng, L. N. Boyle, and J. D. Lee, "Reading, typing, and driving: how interactions with in-vehicle systems degrade driving performance," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 27, pp. 182–191, 2014.

[62] G. Yannis, A. Laiou, P. Papantoniou, and C. Christoforou, "Impact of texting on young drivers' behavior and safety on urban and rural roads through a simulation experiment," *Journal of Safety Research*, vol. 49, pp. 25.e1–31, 2014.

[63] M. M. Haque and S. Washington, "The impact of mobile phone distraction on the braking behaviour of young drivers: a hazard-based duration model," *Transportation Research Part C: Emerging Technologies*, vol. 50, pp. 13–27, 2015/01/01/2015.

[64] G. Rumschlag, T. Palumbo, A. Martin, D. Head, R. George, and R. L. Commissaris, "The effects of texting on driving performance in a driving simulator: the influence of driver age," *Accident Analysis and Prevention*, vol. 74, pp. 145–149, 2015.

[65] I. Pavlidis, "Dissecting driver behaviors under cognitive, emotional, sensorimotor, and mixed stressors," *Scientific Reports*, vol. 6, no. 1, pp. 25651–25712, 2016.

[66] G. K. Kountouriotis, P. Spyridakos, O. M. J. Carsten, and N. Merat, "Identifying cognitive distraction using steering wheel reversal rates," *Accident Analysis and Prevention*, vol. 96, pp. 39–45, 2016.

[67] M. Papadakaki, G. Tzamalouka, C. Gnardellis, T. J. Lajunen, and J. Chliaoutakis, "Driving performance while using a mobile phone: a simulation study of Greek professional drivers," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 38, pp. 164–170, 2016.

[68] T. Liu, Y. Yang, G. Huang, Y. K. Yeo, and Z. Lin, "Driver distraction detection using semi-supervised machine learning," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 4, pp. 1108–1120, 2016.

[69] W. J. Horrey, M. F. Lesch, A. Garabet, L. Simmons, and R. Maikala, "Distraction and task engagement: how interesting and boring information impact driving performance and subjective and physiological responses," *Applied Ergonomics*, vol. 58, pp. 342–348, 2017.

[70] P. Choudhary and N. R. Velaga, "Analysis of vehicle-based lateral performance measures during distracted driving due to phone use," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 44, pp. 120–133, 2017.

[71] P. Choudhary and N. R. Velaga, "Mobile phone use during driving: effects on speed and effectiveness of driver compensatory behaviour," *Accident Analysis and Prevention*, vol. 106, pp. 370–378, 2017.

[72] C. Streiffer, R. Raghavendra, T. Benson, and M. Srivatsa, "Darnet: a deep learning solution for distracted driving detection," in *Proceedings of the 18th acm/ifip/usenix middleware conference*, pp. 22–28, Industrial track, Las Vegas, NV, USA, December, 2017.

[73] J. A. Yu, Y. D. Chen, and X. Xu, *Sensing Vehicle Conditions for Detecting Driving Behaviors (SpringerBriefs in Electrical and Computer Engineering)*, Springer, Berlin, Germany, 2018.

[74] A. Aksjonov, P. Nedoma, V. Vodovozov, E. Petlenkov, and M. Herrmann, "Detection and evaluation of driver distraction using machine learning and fuzzy logic," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 6, pp. 2048–2059, 2019.

[75] C. Ortiz, S. Ortiz-Peregrina, J. J. Castro, M. Casares-López, and C. Salas, "Driver distraction by smartphone use (WhatsApp) in different age groups," *Accident Analysis and Prevention*, vol. 117, pp. 239–249, 2018.

[76] X. Li, O. Oviedo-Trespalacios, A. Rakotonirainy, and X. Yan, "Collision risk management of cognitively distracted drivers in a car-following situation," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 60, pp. 288–298, 2019.

[77] P. Choudhary and N. R. Velaga, "Driver behaviour at the onset of yellow signal: a comparative study of distraction caused by use of a phone and a music player," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 62, pp. 135–148, 2019.

[78] S. Ahangari, M. Jeihani, and A. Dehzangi, "A machine learning distracted driving prediction model," in *Proceedings of the 3rd International Conference on Vision, Image and Signal Processing*, pp. 1–6, Vancouver, Canada, August, 2019.

[79] R. Torres, O. Ohashi, and G. Pessin, "A machine-learning approach to distinguish passengers and drivers reading while driving," *Sensors*, vol. 19, no. 14, p. 3174, 2019.

[80] M. Gjoreski, M. Z. Gams, M. Lustrek, P. Genc, J. U. Garbas, and T. Hassan, "Machine learning and end-to-end deep learning for monitoring driver distractions from physiological and visual signals," *IEEE Access*, vol. 8, pp. 70590–70603, 2020.

[81] P. Choudhary, N. M. Pawar, N. R. Velaga, and D. S. Pawar, "Overall performance impairment and crash risk due to distracted driving: a comprehensive analysis using structural equation modelling," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 74, pp. 120–138, 2020.

[82] A. D. McDonald, T. K. Ferris, and T. Wiener, "Classification of driver distraction: a comprehensive analysis of feature generation, machine learning, and input measures," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 62, no. 6, pp. 1019–1035, 2020.

[83] S. Yang, J. Kuo, and M. G. Lenné, "Effects of distraction in on-road level 2 automated driving: impacts on glance behavior and takeover performance," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 63, no. 8, pp. 1485–1497, 2020.

[84] S. Ahangari, M. Jeihani, B. Salahshour, and M. Ndegwa, "A comprehensive analysis of distracted driving using a driving simulator," *International Journal of Traffic and Transportation Engineering*, vol. 10, no. 2, pp. 252–265, 2020.

[85] L. Li, B. Zhong, C. Hutmacher, Y. Liang, W. J. Horrey, and X. Xu, "Detection of driver manual distraction via image-based hand and ear recognition," *Accident Analysis ands Prevention*, vol. 137, Article ID 105432, 2020.

[86] M. Shahverdy, M. Fathy, R. Berangi, and M. Sabokrou, "Driver behavior detection and classification using deep convolutional neural networks," *Expert Systems with Applications*, vol. 149, Article ID 113240, 2020.

[87] J. C. Chen, C. Y. Lee, P. Y. Huang, and C. R. Lin, "Driver behavior analysis via two-stream deep convolutional neural network," *Applied Sciences*, vol. 10, pp. 1908–1916, 2020.

[88] S. Ahangari, M. Jeihani, M. M. Rahman, and A. Dehzangi, "Predicting driving distraction patterns in different road classes using a support vector machine," *International Journal of Traffic and Transportation Engineering*, vol. 11, no. 1, pp. 102–114, 2021.

[89] J. Son and M. Park, "The effects of distraction type and difficulty on older drivers' performance and behaviour: visual vs. Cognitive," *International Journal of Automotive Technology*, vol. 22, no. 1, pp. 97–108, 2021.

[90] K. Iio, X. Guo, and D. Lord, "Examining driver distraction in the context of driving speed: an observational study using disruptive technology and naturalistic data," *Accident Analysis and Prevention*, vol. 153, Article ID 105983, 2021.

[91] X. Rao, F. Lin, Z. Chen, and J. Zhao, "Distracted driving recognition method based on deep convolutional neural network," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 1, pp. 193–200, 2021.

[92] M. Aljasim and R. Kashef, "E2DR: a deep learning ensemble-based driver distraction detection with recommendations model," *Sensors*, vol. 22, no. 5, p. 1858, 2022.

[93] X. Zuo, C. Zhang, F. Cong, J. Zhao, and T. Hämäläinen, "Driver distraction detection using bidirectional long short-term network based on multiscale entropy of EEG," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 10, pp. 19309–19322, 2022.

[94] N. Zangi, R. Srour-Zreik, D. Ridel, H. Chassidim, and A. Borowsky, "Driver distraction and its effects on partially automated driving performance: a driving simulator study among young-experienced drivers," *Accident Analysis and Prevention*, vol. 166, Article ID 106565, 2022.

[95] M. U. Hossain, M. A. Rahman, M. M. Islam, A. Akhter, M. A. Uddin, and B. K. Paul, "Automatic driver distraction detection using deep convolutional neural networks," *Intelligent Systems with Applications*, vol. 14, Article ID 200075, 2022.

[96] P. Papantoniou, C. Antoniou, E. Papadimitriou, G. Yannis, and J. Golias, "Exploratory analysis of the effect of distraction on driving behaviour through a driving simulator experiment," in *Proceedings of the 6th Pan-Hellenic Road Safety Conference*, Hellenic Institute of Transportation Engineers, National Technical University of Athens, Athens, Greece, March, 2015.

[97] S. Hallmark, *Initial Analyses From the SHRP 2 Naturalistic Driving Study: Addressing Driver Performance And Behavior In Traffic Safety (Transportation Research Board National Academies of Sciences, Engineering, Medicine)*, The National Academies Press, Washington, DC, 2013.

[98] O. Carsten, "Driver distraction and inattention," https://erticonetwork.com/wp-content/uploads/2017/12/UDRIVE-D43.1-Driver-distraction-and-inattention.pdf.

[99] K. L. Campbell, "The SHRP 2 naturalistic driving study: addressing driver performance and behavior in traffic safety," *Truck News*, vol. 282, 2012.

[100] S. Alghnam, J. Towhari, M. Alkelya, A. Binahmad, and T. M. Bell, "The effectiveness of introducing detection cameras on compliance with mobile phone and seatbelt laws: a before-after study among drivers in Riyadh, Saudi Arabia," *Injury epidemiology*, vol. 5, no. 1, pp. 31–38, 2018.

[101] T. A. Ranney, J. L. Harbluk, and Y. I. Noy, "Effects of voice technology on test track driving performance: implications for driver distraction," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 47, no. 2, pp. 439–454, 2005.

[102] Y.-H. Chang, C.-S. Liao, and W.-H. Chieng, "Optimal motion cueing for 5-DOF motion simulations via a 3-DOF motion simulator," *Control Engineering Practice*, vol. 17, no. 1, pp. 170–184, 2009.

[103] A. Mohammadi, S. Asadi, K. Nelson, and S. Nahavandi, "Future reference prediction in model predictive control based driving simulators," in *Proceedings of the Australasian conference on robotics and automation (ACRA2016)*, Brisbane, Australia, December, 2016.

[104] M. Luzuriaga, S. Trunzer, and B. Schick, "A missing link between fidelity and realism: an ex-perts' assessment about an advanced motion-based driv-ing simulator," *International Journal of Vehicle Systems Modelling and Testing*, vol. 15, no. 2-3, 2020.

[105] I. Siegler, G. Reymond, A. Kemeny, and A. Berthoz, "Sensorimotor integration in a driving simulator: contributions of motion cueing in elementary driving tasks," in *Proceedings of the driving simulation conference*, pp. 21–32, Strasbourg, France, September, 2001.

[106] A. P. Newton and M. Best, "The influence of motion on handling dynamics analysis in full vehicle simulators," in *Proceedings of the 8th International Symposium on Advanced Vehicle Control (AVEC)*, Taipei, Taiwan, August, 2006.

[107] K. Takeda, *In-vehicle Corpus and Signal Processing for Driver Behavior*, Springer, Berlin, Germany, 2009.

[108] K. A. Brookhuis and D. de Waard, "Monitoring drivers' mental workload in driving simulators using physiological measures," *Accident Analysis and Prevention*, vol. 42, no. 3, pp. 898–903, 2010.

[109] Y. Sun, X. Yu, J. Berilla, Z. Liu, and G. Wu, "An in-vehicle physiological signal monitoring system for driver fatigue detection," in *Proceedings of the 3rd International Conference on Road Safety and SimulationPurdue University Transportation Research Board*, Indianapolis, Indiana, September, 2011.

[110] H. Fruhstorfer and R. Bergström, "Human vigilance and auditory evoked responses," *Electroencephalography and Clinical Neurophysiology*, vol. 27, no. 4, pp. 346–355, 1969.

[111] E. M. Peck, D. Afergan, B. F. Yuksel, F. Lalooses, and R. J. Jacob, "Using fNIRS to measure mental workload in the real world," in *Advances in Physiological Computing*, pp. 117–139, Springer, Berlin, Germany, 2014.

[112] F. Flemisch, "Towards highly automated driving: intermediate report on the haveit-joint system," in *Proceedings of the 3rd European Road Transport Research Arena, TRA 2010*, Brussels, Belgium, June, 2010.

[113] J. Snider, "DistractionHangover: characterization of the delayed return to baseline driving risk after distracting behaviors," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 65, no. 2, pp. 306–320, 2021.

[114] X. Li, A. Rakotonirainy, X. Yan, and Y. Zhang, "Driver's visual performance in rear-end collision avoidance process under the influence of cell phone use," *Transportation Research Record*, vol. 2672, no. 37, pp. 55–63, 2018.

[115] O. Oviedo-Trespalacios, A. P. Afghari, and M. M. Haque, "A hierarchical Bayesian multivariate ordered model of distracted drivers' decision to initiate risk-compensating behaviour," *Analytic Methods in Accident Research*, vol. 26, Article ID 100121, 2020.

[116] A. Pauzié, "A method to assess the driver mental workload: the driving activity load index (DALI)," *IET Intelligent Transport Systems*, vol. 2, no. 4, pp. 315–322, 2008.

[117] J. Reason, A. Manstead, S. Stradling, J. Baxter, and K. Campbell, "Errors and violations on the roads: a real distinction?" *Ergonomics*, vol. 33, no. 10-11, pp. 1315–1332, 1990.

[118] E. T. Solovey, M. Zec, E. A. Garcia Perez, B. Reimer, and B. Mehler, "Classifying driver workload using physiological and driving performance data: two field studies," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 4057–4066, Montréal, Canada, April, 2014.

[119] K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: a review," *Sensors*, vol. 18, no. 8, p. 2674, 2018.

[120] M. I. Jordan and T. M. Mitchell, "Machine learning: trends, perspectives, and prospects," *Science*, vol. 349, no. 6245, pp. 255–260, 2015.

[121] B. Mahesh, "Machine learning algorithms-A review," *International Journal of Science and Research (IJSR)*, vol. 9, pp. 381–386, 2020.

[122] A. E. Maxwell, T. A. Warner, and F. Fang, "Implementation of machine-learning classification in remote sensing: an applied review," *International Journal of Remote Sensing*, vol. 39, no. 9, pp. 2784–2817, 2018.

[123] S. B. Kotsiantis, I. Zaharakis, and P. Pintelas, "Supervised machine learning: a review of classification techniques," *Emerging artificial intelligence applications in computer engineering*, vol. 160, no. 1, pp. 3–24, 2007.

[124] A. Liaw and M. Wiener, "Classification and regression by randomForest," *R News*, vol. 2, no. 3, pp. 18–22, 2002.

[125] M. Haque and S. Washington, "Stopping behaviour of drivers distracted by mobile phone conversations," in *Proceedings of the Australasian Transport Research Forum 2013 Proceedings*, pp. 1–15, Australasian Transport Research Forum (ATRF), Brisbane, Australia, October, 2013.

[126] A. B. Ünal, L. Steg, and K. Epstude, "The influence of music on mental effort and driving performance," *Accident Analysis and Prevention*, vol. 48, pp. 271–278, 2012/09/01/2012.

[127] C. Bottom and R. Ashworth, "Factors affecting the variability of driver gap-acceptance behaviour," *Ergonomics*, vol. 21, no. 9, pp. 721–734, 1978.

[128] H. V. Jones and N. W. Heimstra, "Ability of drivers to make critical passing judgments," *Journal of engineering psychology*, vol. 3, no. 4, pp. 117–122, 1964.

[129] M. M. Haque and S. Washington, "Effects of mobile phone distraction on drivers' reaction times," *Journal of the Australasian College of Road Safety*, vol. 24, no. 3, pp. 20–29, 2013.

[130] B. Mehle, B. Reimer, and Y. Wang, "A comparison of heart rate and heart rate variability indices in distinguishing single-task driving and driving under secondary cognitive workload," in *Proceedings of the Sixth International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design (Driver Assessment)*, Lake Tahoe, CA, USA, June, 2011.

[131] T. A. Schweizer, K. Kan, Y. Hung, F. Tam, G. Naglie, and S. Graham, "Brain activity during driving with distraction: an immersive fMRI study," *Frontiers in Human Neuroscience*, vol. 7, p. 53, 2013.

[132] A. Koohestani, P. M. Kebria, A. Khosravi, and S. Nahavandi, "Drivers awareness evaluation using physiological measurement in a driving simulator," in *Proceedings of the 2019 IEEE International Conference on Industrial Technology (ICIT)*, pp. 859–864, Melbourne, Australia, February, 2019.

[133] H. Almahasneh, W.-T. Chooi, N. Kamel, and A. S. Malik, "Deep in thought while driving: an EEG study on drivers' cognitive distraction," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 26, pp. 218–226, 2014.

[134] C.-T. Lin, S.-A. Chen, L.-W. Ko, and Y.-K. Wang, "EEG-based brain dynamics of driving distraction," in *Proceedings of the 2011 International Joint Conference on Neural Networks*, pp. 1497–1500, IEEE, San Jose, CA, USA, June, 2011.

[135] A. Sonnleitner, "EEG alpha spindles and prolonged brake reaction times during auditory distraction in an on-road driving study," *Accident Analysis and Prevention*, vol. 62, pp. 110–118, 2014.

[136] S. H. Fairclough and L. Mulder, "Psychophysiological processes of mental effort investment," *How motivation affects cardiovascular response: Mechanisms and applications*, American Psychological Association, Washington, DC, USA, 2012.

[137] J. Slob, "State-of-the-art driving simulators, a literature survey," *DCT report*, vol. 107, 2008.

[138] J. A. Houck, R. J. Telban, and F. M. Cardullo, *Motion Cueing Algorithm Development: Human-Centered Linear and Nonlinear Approaches*, CreateSpace Independent Publishing Platform, Scotts Valley, CA, USA, 2005.

[139] Y. Zou, Y. Zhang, and K. Cheng, "Exploring the impact of climate and extreme weather on fatal traffic accidents," *Sustainability*, vol. 13, no. 1, p. 390, 2021.
[140] Y. Liu, Y. Zou, Y. Wang, and B. Wu, "Impact of fog conditions on lane-level speeds on freeways," *Journal of Transportation Engineering, Part A: Systems*, vol. 146, no. 9, Article ID 04020095, 2020.
[141] S. Jahedi and F. Méndez, "On the advantages and disadvantages of subjective measures," *Journal of Economic Behavior and Organization*, vol. 98, pp. 97–114, 2014.
[142] G. Marshall, "The purpose, design and administration of a questionnaire for data collection," *Radiography*, vol. 11, no. 2, pp. 131–136, 2005.
[143] J. Feng, S. Marulanda, and B. Donmez, "Susceptibility to driver distraction questionnaire: development and relation to relevant self-reported measures," *Transportation Research Record*, vol. 2434, no. 1, pp. 26–34, 2014.
[144] C.-T. Lin, R.-C. Wu, S.-F. Liang, W.-H. Chao, Y.-J. Chen, and T.-P. Jung, "EEG-based drowsiness estimation for safety driving using independent component analysis," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 52, no. 12, pp. 2726–2738, 2005.
[145] M. R. Lakshmi, T. Prasad, and V. C. Prakash, "Survey on EEG signal processing methods," *International Journal of Advanced Research in Computer Science and Software Engineering*, vol. 4, no. 1, 2014.
[146] O. Fy, A. Jet, O. Awodele, J. Hinmikaiye, O. Olakanmi, and J. Akinjobi, "Supervised machine learning algorithms: classification and comparison," *International Journal of Computer Trends and Technology*, vol. 48, no. 3, pp. 128–138, 2017.
[147] S. Ray, "Understanding Support vector machine(SVM) algorithm from examples (along with code)," 2017, https://www.analyticsvidhya.com/blog/2017/09/understaing-support-vector-machine-example-code/.
[148] S. Ray, "A quick review of machine learning algorithms," in *Proceedings of the 2019 International conference on machine learning, big data, cloud and parallel computing (COMITCon)*, pp. 35–39, IEEE, Faridabad, India, February, 2019.
[149] A. Vidhya, "Tree based algorithms: a complete tutorial from scratch (in R & Python)," 2016, https://www.analyticsvidhya.com/blog/2016/04/tree-based-algorithms-complete-tutorial-scratch-in-python/#nine.
[150] D. Trehan, "Why choose random forest and not decision trees," 2020, https://towardsai.net/p/machine-learning/why-choose-random-forest-and-not-decision-trees.
[151] S. R. Mousa, P. R. Bakhit, O. A. Osman, and S. Ishak, "A comparative analysis of tree-based ensemble methods for detecting imminent lane change maneuvers in connected vehicle environments," *Transportation Research Record*, vol. 2672, no. 42, pp. 268–279, 2018.
[152] H. Musa, B. Modi, I. Abdulkarim Adamu, A. A. Aminu, H. Adamu, and Y. Ajiya, "AComparative analysis of different feature set on the performance of different algorithms in phishing website detection," *International Journal of Artificial Intelligence and Applications*, vol. 10, no. 03, pp. 41–47, 2019.
[153] C. Bentéjac, A. Csörgő, and G. Martínez-Muñoz, "A comparative analysis of gradient boosting algorithms," *Artificial Intelligence Review*, vol. 54, no. 3, pp. 1937–1967, 2021.
[154] C. Yan, F. Coenen, and B. Zhang, "Driving posture recognition by convolutional neural networks," *IET Computer Vision*, vol. 10, no. 2, pp. 103–114, 2016.
[155] D. Tran, H. Manh Do, W. Sheng, H. Bai, and G. Chowdhary, "Real-time detection of distracted driving based on deep learning," *IET Intelligent Transport Systems*, vol. 12, no. 10, pp. 1210–1219, 2018.
[156] M. S. Majdi, S. Ram, J. T. Gill, and J. J. Rodríguez, "Drive-net: convolutional network for driver distraction detection," in *Proceedigns of the 2018 IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI)*, pp. 1–4, IEEE, Las Vegas, NV, USA, April, 2018.
[157] R. Vargas, A. Mosavi, and R. Ruiz, *Deep Learning: A Review*, 2017,https://www.researchgate.net/publication/318447392_DEEP_LEARNING_A_REVIEW.
[158] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in Neural Information Processing Systems*, vol. 25, 2012.
[159] S. Chaib, H. Yao, Y. Gu, and M. Amrani, "Deep feature extraction and combination for remote sensing image classification based on pre-trained CNN models," in *Proceedings of the Ninth international conference on digital image processing (ICDIP 2017)*, vol. 10420, p. 104203D, International Society for Optics and Photonics, Hong Kong, China, May, 2017.
[160] R. Miotto, F. Wang, S. Wang, X. Jiang, and J. T. Dudley, "Deep learning for healthcare: review, opportunities and challenges," *Briefings in Bioinformatics*, vol. 19, no. 6, pp. 1236–1246, 2018.
[161] H. Hagras, "Toward human-understandable, explainable AI," *Computer*, vol. 51, no. 9, pp. 28–36, 2018.
[162] S. Wachter, B. Mittelstadt, and L. Floridi, "Transparent, explainable, and accountable AI for robotics," *Science Robotics*, vol. 2, no. 6, p. eaan6080, 2017.
[163] K. Siau and W. Wang, "Artificial intelligence (AI) ethics: ethics of AI and ethical AI," *Journal of Database Management*, vol. 31, no. 2, pp. 74–87, 2020.
[164] O. Oviedo-Trespalacios, M. M. Haque, M. King, and S. Washington, "Effects of road infrastructure and traffic complexity in speed adaptation behaviour of distracted drivers," *Accident Analysis and Prevention*, vol. 101, pp. 67–77, 2017.